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# Heterogeneous patterns enhancing static and dynamic texture classification

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**Abstract.** Some mixtures, such as colloids like milk, blood, and gelatin, have homogeneous appearance when viewed with the naked eye, however, to observe them at the nanoscale is possible to understand the heterogeneity of its components. The same phenomenon can occur in pattern recognition in which it is possible to see heterogeneous patterns in texture images. However, current methods of texture analysis can not adequately describe such heterogeneous patterns. Common methods used by researchers analyse the image information in a global way, taking all its features in an integrated manner. Furthermore, multi-scale analysis verifies the patterns at different scales, but still preserving the homogeneous analysis. On the other hand various methods use textons to represent the texture, breaking texture down into its smallest unit. To tackle this problem, we propose a method to identify texture patterns not small as textons at distinct scales enhancing the separability among different types of texture. We find sub patterns of texture according to the scale and then group similar patterns for a more refined analysis. Tests were performed in four static texture databases and one dynamical one. Results show that our method provide better classification rate compared with conventional approaches both in static and in dynamic texture.

## 1. Introduction

Pattern recognition is the identification and interpretation of patterns in images, in order to extract relevant information on the image to identify and classify your content. Classification of patterns can be used in a variety of applications in different fields such as nanotechnology [1, 2], biology [3, 4], medicine [5] and computer science [6, 7]. Different approaches are developed according to the application, however, most of them analyze the information in a global way, using all the features in an integrated manner. One side in the pattern classification approach uses multi-scale analysis of patterns, that is, different scales of observation are used to perform the analysis and find similar patterns, because important structures in an image usually occur at different spatial scales [8] [9]. Methods based on textons [10, 11] represent each pixel of a texture as the convolution of a multi-scale and multi-orientation filter bank producing a texton vocabulary. Thus, these methods of texture analysis characterize the image homogeneously on the scale to be analyzed. Both the overall analysis, such as multi-scale approach is appropriate for the vast majority of problems in image analysis and pattern recognition. However, in some problems, due to the heterogeneous nature of the composition of the objects under consideration, is needed one more step in the process of pattern recognition, analysis of heterogeneous patterns.

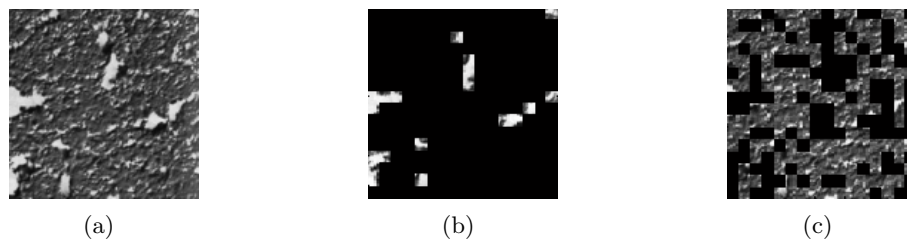
The aim of this paper is to demonstrate how can apply heterogeneous analysis to improve results regarding the homogeneous analysis. To validate our proposal experiments were performed on four static e one dynamic texture databases using the same texture descriptor but with different approaches. In all tests, heterogeneous analysis proved to be better than the homogeneous analysis enhancing the rate classification.

This paper is organized as follows: Section 2 describes the heterogeneous pattern analysis. Section 3 shows the results and discussions and in Section 4 the conclusions.

## 2. Method

Heterogeneous pattern arises when the object under analysis presents combined patterns in its composition. Similar to the classic definition of heterogeneous compositions in chemical compounds [12], which is the characteristic of presenting a different appearance or composition when analyzed in parts. The same analogy can be applied in recognizing patterns in images. In each image can be found heterogeneous patterns, i. e., it is possible to distinguish the different patterns in each of the texture images. Figure 1(a) shows an image from Brodatz, which analyzed by conventional methods, would be defined only a pattern for this image. Using the approach of heterogeneous patterns, two different types of texture patterns are identified in its formation.

This new view to analyze the various patterns requires a new approach for analysis of similarity between images. The first step is to segment the texture by defining regions where the image belong to a given pattern while defining the patterns in the image. Figures 1(b) and 1(c) illustrate the segmentation of the image of Figure 1(a) in two of patterns.

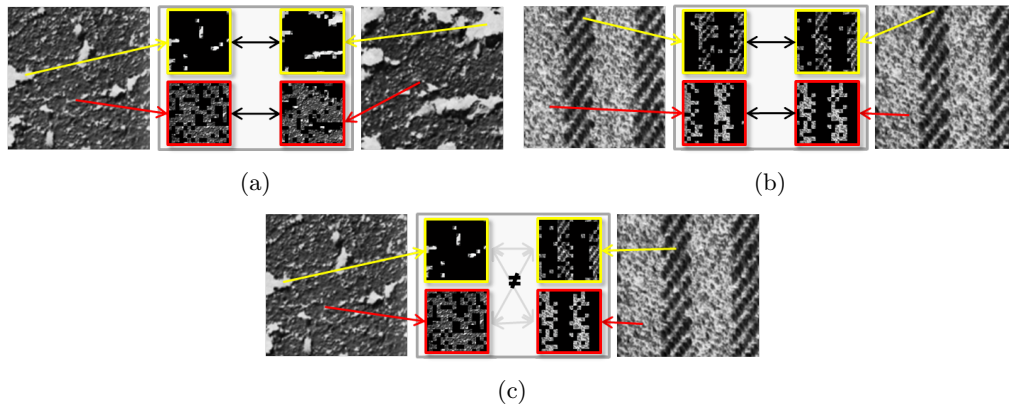


**Figure 1.** Segmentation according to the heterogeneous patterns. (a) Original image. (b) and (c) Two patterns obtained from (a).

To obtain this result the image was divided into smaller sized windows of  $8 \times 8$  pixels, for windows with texture sufficiently homogeneous, that is, where only one pattern is found. Furthermore, there was obtained a characteristic to represent each window. Windows with similar characteristics remain the same pattern, and those with distinct characteristics were separated into different patterns. Figures 1(b) and 1(c) show the windows stayed grouped using *k-means* algorithm according to their pattern with the remaining windows in each pattern. Textural features from Haralick [13] descriptors were used to characterize each window. Contrast, Correlation, Energy and Homogeneity were computed from resulting co-occurrence matrices to obtain a set of 32 descriptors for each window. Distances of 1 and 2 pixels with angles of  $0^\circ$ ,  $45^\circ$ ,  $90^\circ$  and  $135^\circ$  were used.

After the windows were divided into patterns, we performed a survival analysis of windows, 25% of the windows with features farthest from the group average were discarded making the representation of pattern more consistent. Each pattern was characterized by a feature vector average that is the average of the characteristics of all windows belonging to the pattern. The next step is to find the best matching among the patterns to define the image similarity as Figures 2(a) and 2(b) exemplify. They show two examples where it has an optimal matching among the image patterns of the same class. When you find the best fit among all the patterns

in each image, we have the degree of similarity, defining whether the images belong to the same class. Figure 2(c) shows an example where it is not possible to perform the fitting patterns and all possibilities of fitting are tested. That's why the images belong to different classes.



**Figure 2.** Matching patterns. (a) and (b) matching of two images from the same class. (c) Matching of patterns can not be made because the images belong to different classes.

### 3. Results and Discussions

To validate the method of analysis for heterogeneous patterns, this technique was applied in four different texture databases, each with its peculiarities: Brodatz, USPTex, Vistex and Outex and one dynamic texture database: Dyntex. Figure 3 shows some samples of these databases. The classification method  $k$ -Nearest Neighbor ( $k - NN$ ) with 10-fold cross-validation scheme was used in all experiments.

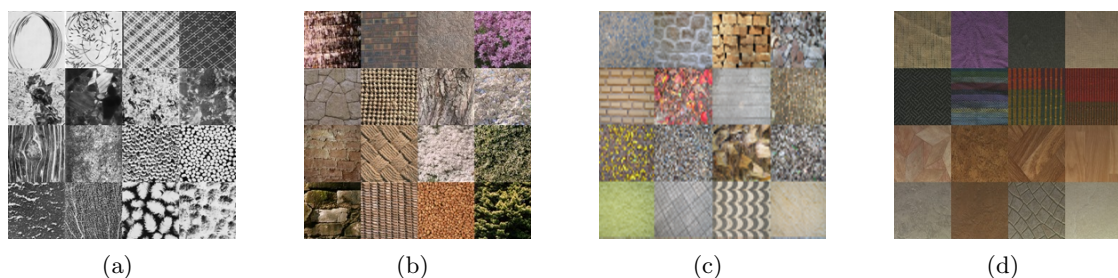
**Brodatz** [14] contains 1110 natural textures of  $200 \times 200$  pixels divided into 111 classes.

**Vistex** [15] contains 864 images of  $128 \times 128$  pixels size with 54 texture classes.

**USPTex** has 3984 natural texture images of  $128 \times 128$  pixels size divided into 332 classes.

**Outex** [16] has 1360 images of  $128 \times 128$  pixels size divided into 68 classes.

**Dyntex** [17] consists of 1230 videos with 250 frames with  $400 \times 300$  pixels size divided into 123 classes of dynamic texture.



**Figure 3.** (a) Brodatz. (b) Vistex. (c) Usptex. (d) Outex.

The method used as classical approach was Haralick descriptors with the same configurations of characterization of windows. This way we can compare the same descriptor but with different

**Table 1.** Accuracy rate by comparing the traditional method of analysis with the heterogeneous method.

| Database              | Brodatz | Vistex | Usptex | Outex | Dyntex |
|-----------------------|---------|--------|--------|-------|--------|
| Classical approach    | 88.92   | 89.47  | 69.58  | 76.62 | 76.89  |
| Heterogeneous pattern | 93.06   | 93.63  | 78.49  | 76.99 | 98.29  |

perspectives. One of the most important parameters is the window size that directly interferes in the results. Large windows remain with the general representation of the image, preserving the homogeneous analysis of patterns. However, becomes more homogeneous window, or small windows, the classification rate increases, as the representative pattern of the window increases. For this experiment two patterns were analyzed in each image. Table 1 shows the results obtained when using the conventional method in comparison with heterogeneous patterns, in all cases heterogeneous pattern method improved the classification rate proving to be better than the standard approach in which only one pattern is established for the entire image.

#### 4. Conclusions

Usually, analysis in texture pattern recognition using the homogeneous approach taking all the image information in a global way, that is, the entire image is defined as one pattern. However, it is possible to find more than one texture pattern on the image that we called here, heterogeneous pattern. It is necessary to map the patterns in each image and then check the similarity of patterns among them. This method improved the accuracy rate of classification using the same method to characterize the image showing robustness to assess patterns heterogeneous image.

#### References

- [1] Annampedu V and Wagh M D 2007 *Microelectronics Journal* **38** 430 – 438 ISSN 0026-2692
- [2] Oh E H, Song H S and Park T H 2011 *Enzyme and Microbial Technology* **48** 427 – 437 ISSN 0141-0229
- [3] Galas D J, Eggert M and Waterman M S 1985 *Journal of Molecular Biology* **186** 117 – 128 ISSN 0022-2836
- [4] Isasi A G, Zapirain B G and Zorrilla A M 2011 *Computers in Biology and Medicine* **41** 742 – 755 ISSN 0010-4825
- [5] Landeweerd G, Gelsema E, Bins M and Halie M 1981 *Pattern Recognition* **14** 239 – 244 ISSN 0031-3203
- [6] Este A, Gringoli F and Salgarelli L 2009 *Comput. Netw.* **53**(14) 2476–2490 ISSN 1389-1286
- [7] Canals V, Morro A and Rossell J L 2010 *Pattern Recognition Letters* **31** 2353 – 2356 ISSN 0167-8655
- [8] Koenderink J 1984 *Biological Cybernetics* **50**(5) 363–370 ISSN 0340-1200 10.1007/BF00336961
- [9] Witkin A P 1983 Scale-space filtering *IJCAI* pp 1019–1022
- [10] Julesz B 1981 *Nature* **290** 91–97
- [11] Leung T and Malik J 1999 Recognizing surfaces using three-dimensional textons *Computer Vision, 1999. The Proceedings of the Seventh IEEE International Conference on* vol 2 pp 1010–1017
- [12] Staley D D, Matta M S and Waterman E L 2004 *Chemistry* (Pearson Prentice Hall)
- [13] Haralick R M, Shanmugam K and Dinstein I 1973 *Systems, Man and Cybernetics, IEEE Transactions on* **3** 610 –621 ISSN 0018-9472
- [14] Brodatz P 1966 *Textures; a photographic album for artists and designers* (Dover Publications New York,) ISBN 0486216691
- [15] 2009 Vision texture database URL [vismod.media.mit.edu/vismod/imagery/VisionTexture/vistex.html](http://vismod.media.mit.edu/vismod/imagery/VisionTexture/vistex.html)
- [16] Ojala T, Mäenpää T, Pietikäinen M, Viertola J, Kyllönen J and Huovinen S 2002 Outex - new framework for empirical evaluation of texture analysis algorithms *Proceedings of the 16 th International Conference on Pattern Recognition (ICPR'02) Volume 1 - Volume 1* ICPR '02 (Washington, DC, USA: IEEE Computer Society) p 10701 ISBN 0-7695-1695-X
- [17] Péteri R, Fazekas S and Huiskes M J 2010 *Pattern Recognition Letters* **31** 1627–1632 <http://projects.cwi.nl/dyntex/>